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Improvement Heuristics for Manufacturing System Design Using Complex Network Figures

Henning Blunck[a], Victor Vican[a], Till Becker[a]*, Katja Windt[a]

[a]*Global Production Logistics Workgroup, Jacobs University Bremen, Campus Ring 1, 28759 Bremen, Germany*

* Corresponding author. Tel.:+49-421-200-3074; fax: +49-421-200-3078. *E-mail address:* t.becker@jacobs-university.de

Abstract

Today's manufacturing systems are characterized by a high level of structural complexity, accompanied by a diverse, less uniform material flow. As this contribution will show, this development complicates the identification of work stations that limit the logistic target achievement, because the non-trivial network effects are hard to predict. However, this identification of key work stations is particularly important during the design and operation phase of a manufacturing system, as they allow a cost-optimal system improvement with limited inference on the operation. Our approach discusses the "bottleneck" oriented approach commonly applied today in the context of network effects in manufacturing systems and compares its performance to centrality measures from complex network theory.

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1. Introduction

Many companies face increasing competition in global markets. The worldwide availability of products increases customer expectations regarding quality, delivery time, and product variability. Especially the increased variability, caused by the trend of mass customization, causes significant additional amount of complexity in supply chains and manufacturing systems, because a greater product variety induces the need for a greater variety of resources and processes in production, storage, and administration [1].

In its basic form, a manufacturing system consists of a set of processing elements (e.g., work stations, buffers, quality gates) and their interconnections defined by the material flow between them [2]. The aforementioned increase in product variety leads to an increase in the number of work stations on the one hand, and to an increase in the number of distinct material flow connections on the shop floor on the other hand. This increase in number of both entities and connections among them is commonly considered as a sign of increasing structural complexity [1,3]. In the presence of non-negligible setup times, additional product variety may also induce an increase in dynamic, i.e. time-related, complexity, as it creates time-dependent, non-stationary material flows between the work stations. This increasing complexity impedes a functional understanding of the planned or existing manufacturing system by the designer or operator, which is fundamental to devise and implement directed, effective performance improvement measures [4].

By system performance, we refer to the degree of efficiency the manufacturing system can attain, measured in low inventory levels and high resource utilization, as well as the level of service it can provide to downstream customers, measured in high due date reliability and low lead times [5]. A driver of efficiency in manufacturing system design and control is the identification of performance limiting resources in the system, commonly referred to as *bottlenecks* [6-8]. As Wang et al. [8] point out, there are multiple definitions and detection methods for bottlenecks. In the context of ever tougher market demands and competition, it makes sense to apply a sensitivity based definition for the scope of this contribution, focusing on the "bottom-

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line" system performance, rather than those of individual resources. We define a bottleneck hence as the "machine whose throughput mostly affects the overall system throughput" [8], which poses the challenge of predicting overall system behavior as a function of local changes. In this paper, we will discuss the applicability of heuristics, "rules of thumb", to guide the designer or manager of manufacturing system to the bottleneck. More generally, we will treat these heuristics as a mapping that assigns work stations a value on the real axis under the assumption, that the so established order among the work stations matches the extent by which they impede system performance.

The commonly used approach to select the work station with the highest utilization or longest waiting time as the bottleneck (hereinafter referred to as the utilization-bottleneck heuristic) [7,8] is widely used to replace time-consuming [9] simulation studies in the design and improvement of manufacturing systems [8]. As a source for additional heuristics, we consult complex network theory, which offers the desirable characteristics: Its modeling effort is relatively low, while it is designed to depict the interactions in complex systems of arbitrary scale. It is widely used in social sciences [10-12], but also in natural sciences like biology [13] and in engineering [10]. Regarding logistics, it has been used in supply chain management [14], but its application in manufacturing systems is still sparse.

Our approach is structured as follows: in Section 2, we integrate the identification and alleviation of bottlenecks into the process of manufacturing system design and improvement. Section 3 introduces topological network measures, which are investigated as suitable candidates for bottleneck identification in manufacturing systems. A case study investigates the performance of the selected measures in Section 4. In Section 5, we summarize and conclude our findings.

2. Manufacturing System Design and Bottleneck Alleviation

2.1. Manufacturing System Design

Manufacturing systems design typically focuses on resource requirements, factory layout, the material flow, and capacity planning [15]. Factory layout and material flow design are concerned with the organization of the production processes on the shop floor in, e.g., cellular systems, job shops, project shops, flow production, etc. Detecting performance limiting resources in the design phase hence involves focusing on production capacity and resource requirements.

Common techniques for manufacturing system design and analysis are simulation [8,9], queuing theory [16] or axiomatic design [4,17]. However, with a growing size of the solution space (determined through work stations, material flows, product types, etc.), these methods are known to become computationally intense; here, heuristics, like the aforementioned utilization-bottleneck heuristic, are applied to limit the solution space and to increase the efficiency of the solution space evaluation [18].

2.2. Forms of Bottleneck Alleviation

Various recommendations to deal with a (suspected) bottleneck are available [c.f. 7]. Wiendahl [19] presents a methodological overview to match capacity supply and demand, including capacity adjustments of the workforce or resources, load adjustments through outsourcing, and load balancing through batching, load-shifting, or switching to alternate work stations.

We focus on two measures namely (1) capacity increase and (2) batching to improve capacity utilization by reducing setup times (thus increasing the share of effective processing time, often referred to as Overall Equipment Effectiveness, or OEE), because of their distinct effect on both the company's bottom line and the material flow in the production system. Capacity increase (i.e., adding a second server) increases throughput and reduces queue length, but comes at the cost of increased investment. Batching increases OEE by reducing setup times, but induces time-related (dynamic) complexity in the form of batches, which causes waiting times at downstream work stations. It is a deviation from the otherwise recommended FIFO prioritization rule.

As subsequent analyses will show, different bottleneck alleviation rules influence the material flow patterns, which in turn have an impact on the predictive power of bottleneck heuristics.

3. Complex Network Figures as Network Evaluation Methods

Most complex systems may be reduced to a set of nodes, connected through directed and/or undirected vertices, depending on definition. In social networks, nodes and vertices commonly represent human beings and their relationships, in natural sciences nodes and vertices could be atoms and bonds. A range of applications and network theoretic translations from transportation, supply chains, the service sector, energy, and other fields can be found in [10].

For this paper and in a manufacturing context, we define the manufacturing system as a directed graph ***G*** *= (V, E)* with work stations as nodes *(ws ∈ V)* and material flows as vertices *(e ∈ E)*, connecting two nodes ws_i and ws_k, given that a material flow has occurred or can occur between the two nodes (see Fig. 1).

Equation (1) shows the node-node adjacency matrix representation of resources and flows in an arbitrary production line network, where matrix elements represent unweighted edges with Boolean magnitude as set out in (2).

$$A = \begin{bmatrix} a_{1,1} & a_{1,2} & \cdots & a_{1,n} \\ a_{2,1} & a_{2,2} & \cdots & a_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n,1} & a_{n,2} & \cdots & a_{n,n} \end{bmatrix} \tag{1}$$

$$a_{i,k} = \begin{cases} 1 \text{ for a material flow from } \mathrm{ws_i} \; to \; \mathrm{ws_k} \\ 0 \text{ otherwise} \end{cases} \tag{2}$$

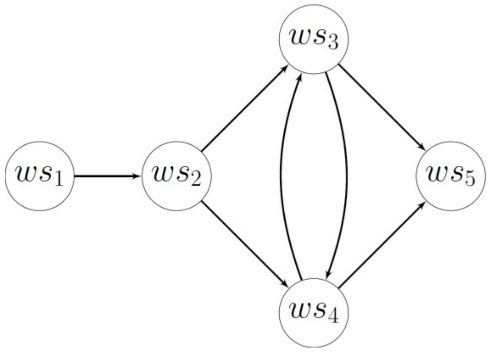

Fig. 1: representative manufacturing system network abstraction

This constitutes the basic architecture of any network and validates the application of network metrics in a manufacturing context. The next section will discuss the fundamentals of network evaluation methods and present their relevance in detecting bottlenecks as improvement heuristics in the design phase.

3.1. Network metrics

Next to the basic characteristics of networks like order and size, various social sciences-rooted [10] analysis methods exist to evaluate networks. The majority of these metrics focuses on concepts of centrality, which are (non-exclusively) summarized in [10-12] and include closeness, betweenness, eigenvector, and degree centrality. Other metrics for different properties include the clustering coefficient, density, and proximity ratio. The magnitudes of each of these metrics indicate the network topology and underlying flow types. Borgatti [11] shows that some metrics may not be uniquely applicable to any network. An example from [11] is the propagation of gossip through a social network, in which undirected links are likely to be visited only once, whereas nodes can be visited many times. Similarly in a manufacturing environment, a job-shop production can allow for multiple visiting of a node along undirected vertices, contrary to transfer-line productions with single node visits along directed vertices. So for example in applying betweenness centrality, Borgatti [11] hypothesizes that objects must flow along shortest paths (geodesics) between two known start and end points. In a flow-shop manufacturing environment this can be a valid assumption for the use of betweenness centrality.

Using a network metric that makes appropriate assumptions about the material flow will therefore significantly support the designer's ability to identify real bottlenecks in the system. In a manufacturing context and using the definition of bottlenecks from [8], bottleneck work stations will tend to be those with a high relative importance, and the concept from network theory most closely related to this is centrality.

3.2. Network metrics in an applied manufacturing context

We implement three measures of centrality for this contribution: node degree, betweenness centrality, and PageRank. The first measure applied is the degree of a work station k, which measures its in- and outbound vertices and is defined as:

$$C_D(ws_k) = \sum_{i=1}^{n} a_{i,k} + \sum_{i=1}^{n} a_{k,i} \tag{3}$$

The degree of a node in a manufacturing network is an intuitive way to determine potential bottlenecks, as it measures the number of connected work stations on the shop floor. When edges are weighted with the (relative) workload traversing along, the classic, utilization based heuristic to find the bottleneck (the work station with the highest utilization) can be calculated as a network statistic as well: As the ratio of sum of weighted inbound edges and node capacity. We will use this approach in our case study in Section 4, but also investigate the (unweighted) node-degree statistic as a bottleneck heuristic, that also takes downstream work stations into consideration. As per equation (3), with an increasing magnitude of $C_D(ws_k)$ relative to the C_D of all other $ws \in V$, the likelihood of work station ws_k being a bottleneck is assumed to increase.

The second metric applied is betweenness centrality, which indicates the share of geodesics g_{ikj} linking ws_i and ws_j that pass through node ws_k in relation to all other g_{ij}.

$$C_b(ws_k) = \sum_{i}^{n} \sum_{j}^{n} \frac{g_{ikj}}{g_{ij}} \tag{4}$$
$$given \ \mathrm{i} \neq \mathrm{j} \neq \mathrm{k}$$

Betweenness centrality indicates the amount of flow that a certain node controls and conversely, of what magnitude the effect would be, given that node would be removed. The analogy to a manufacturing system is the removal of a central work station on the shop floor, which could be equal to a machine-breakdown or set-up and the associated disruptions. Equation (4) again implies an increased likelihood of ws_k being a bottleneck with an increased magnitude of $C_b(ws_k)$ relative to the C_b of all other work stations.

A last measure used in this study is the PageRank algorithm, which indexes a node's importance through unequal counting and normalization of the number of backlinks [20], originally designed to evaluate the importance of web pages in the World Wide Web. In large networks, the PageRank of every node is determined through iterative computation with some initial values by:

$$PR(ws_k) = (1\text{-}d) + d\left(e_{j,k} \cdot \sum_{j=1}^{n} \frac{PR(ws_j)}{c(ws_j)}\right) \tag{5}$$

Where d is a damping factor (a default value of 0.85 has been widely used since its proposition by Page and Brin [20]) that prevents equal distribution of PageRanks over a network. $PR(ws_j)$ denotes the PageRank of a node ws_j, with a directed edge to work station k. $e_{j,k}$ is the weight attribute for the edge between nodes ws_j and ws_k and $c(ws_j)$ is the combined weight of all outgoing edges of ws_j. The PageRank statistic implies that an important work station ws_k passes on its relative importance to other work stations it routes the material flow to, while work station k's own importance increases with an increasing ratio of other work stations' PageRank and the amount of those work stations' material flow is directed towards ws_k. On the shop floor, the PageRank algorithm is expected to determine not only bottleneck work stations, but important direct dependencies of those respective work stations.

3.3. Current network theoretic applications in manufacturing systems design

The application of these network metrics in a shop floor production network has mostly focused on cluster analysis in the design cellular manufacturing systems [21]. With regards to bottleneck rather than cluster identification, Scholz-Reiter et al. [6] use a data-driven network approach to discover dynamic bottlenecks *a posteriori*. However, very little has been done in simulating manufacturing systems as networks to derive *a priori* design specifications on bottleneck identification. Vrabič et al. [22] translate real production data into a manufacturing network and use various network metrics to define the normal operating state of the system and to discover anomalous behavior against the reference operating state. In [23], they translate a manufacturing system into a network model and analyze it with regards to detecting autonomous sub-communities. Other approaches link network measures to performance measures of production feedback data to investigate design implications of the relation between network topology and performance in manufacturing systems [24], or apply a knock-out analysis in a manufacturing network to quantify robustness [2].

General criticism of network theoretic approaches addresses the level of abstraction [25], which makes it hard to derive operational strategies. However, this approach seeks to improve the quality or suggest other ways of calculating systemic bottlenecks. Furthermore, we aim to offer an easy-to-use method for preliminary bottleneck identification, which can be accompanied by more sophisticated methods after the set of possible bottleneck work stations has been narrowed down.

The following section describes how our model assumptions were implemented in a simulation study and gives a comparison of the different metrics chosen in the detection of bottlenecks.

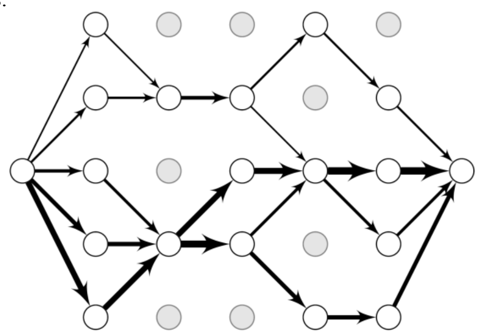

Fig. 2: Sample flow-shop network. Arc widths represent material flow intensities. Unutilized work stations (nodes) are shaded. Artificial start- and end-nodes are also shown.

4. Case Study

As indicated, the determination of the performance limiting bottleneck would require a complete exploration of the solution space, which grows linearly with the number of work stations (as each work station has to be investigated). To test the predictive power of the proposed heuristics, we will do exactly that: We will generate minimal models of flow-shop systems (c.f. Section 4.1) and evaluate their performance when only one work station is altered, according to the alleviation rules in Section 2.2.

4.1. Minimal Flow-Shop Model (Grid)

We will test the ability of the heuristics mentioned in Section 3.2 to guide the designer or operator to the performance-impeding work station, by correlating the work stations' ranking according to the respective heuristics (node-degree, betweenness centrality, and PageRank), with the performance attainable, if only one work station is changed either by increasing its capacity or by batching.

Our investigation focuses on an artificially created grid layout, which serves as a minimal flow-shop example. As we are mainly concerned with network architecture, we model all work stations under the default assumption of capacities of 1 and operations of a workload of 1 (deterministically). To investigate the effect of batching, setup times are set to 0.2 time units, to model switching among different product types. A work station under the batching regime will continue processing a product type, until it has emptied the respective queue. It will then switch to the product type with the longest queue. By default, work stations process jobs on a FIFO basis. The unit workload and capacity allows to measure system performance solely in terms of low throughput times.

We consider a grid layout with five stages and five work stations per stage. Five product variants are randomly assigned to one work station on every stage to be operated on, creating a flow-shop situation. The release rate of product type i is $\alpha^{(i-1)}$ times the release rate of type 1. The flow rate for product type 1 was adjusted, such that the busiest work station had a calculated utilization of about 77% (effective processing, without setup times), to achieve a stable system behavior. By modeling product flows of different intensity, we avoid a trivial and solely setup-induced relationship between in-degree and utilization. Figure 2 shows an exemplary material flow diagram for the described setting. The resulting edge weights were used as weight or cost attributes for the betweenness centrality and PageRank calculations described above. Inter-release times for all product types are then exponentially distributed, with the calculated release rate as the respective mean.

4.2. Simulation Experiments and Results

A total of 800 networks were randomly created and simulated for this contribution. For each network, we calculated the heuristic predictions, using above mentioned formulae and ranked the work stations accordingly. We then started separate simulation runs, with one work station at a time either receiving a capacity increase (doubling the capacity) or switching from FIFO prioritization rule to batching.

We measured the performance in terms of average product throughput time and ranked the results as well (here, a lower average throughput time received a better rank). Given constant release rates, the decrease in throughput time corresponds to a lower WIP and better system performance. For each network and alleviation strategy we then calculated the rank correlation between the predicted ranks by the applied heuristics and the measured system throughput sensitivity according to our simulations.

Measuring and ranking the performance in terms of mean throughput time, when changing a single work station, we can calculate rank correlations between the heuristic predictions and the simulation results. We refer to rank correlations here to express the underlying idea that heuristics should order the work station with respect to their sensitivity for the overall system performance. The histograms of these rank correlations over all 800 investigated networks are shown for $\alpha = 1.4$ in Figure 3 for capacity increase and in Figure 4 for batching. Table 1 gives an overview over the entire investigated parameter space, through key statistics.

Under capacity increase alleviation, the result is clear: The bottleneck heuristic clearly outperforms all other heuristics and even gains in predictive quality with increasing inequality in product flows (PageRank shows the same behavior but on a different absolute level). Under the batching alleviation measure however, the bottleneck heuristic loses clearly in predictive power, in particular for larger values of α. The performance is practically undiscernible from that of the node degree heuristic. Apparently, the batching induced variability in network flows, which increases with the number of product variant processes on that node, supersedes the effect of accounted or ignored edge weights.

The PageRank and betweenness centrality metrics both significantly underperform, in the capacity increase case more dramatically compared to the batching case. The two approaches both account for more than just the direct neighborhood of any work station to calculate the metric. Our results indicate that the performance sensitivity of one worksystem is primarily determined by its direct neighborhood.

The poor performance of the betweenness centrality measure in particular is also likely to result from the pre-determined nature of flows, whereas the betweenness centrality inherently assumes some sort of freedom of choice when it comes to path selection. In that sense, our results give analytical evidence to Borgatti's [11] hypothesis of the non-universal applicability of measures of network centrality to flow types.

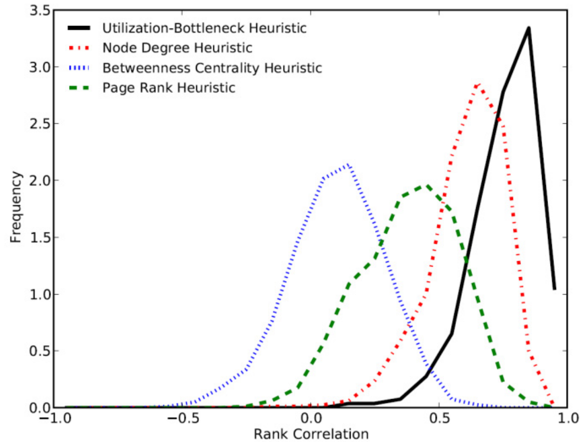

Fig. 3: Histogram of Rank Correlations between work system order predicted by heuristics and order of work systems in terms of throughput enhancement, when capacity was increased ($\alpha = 1.4$).

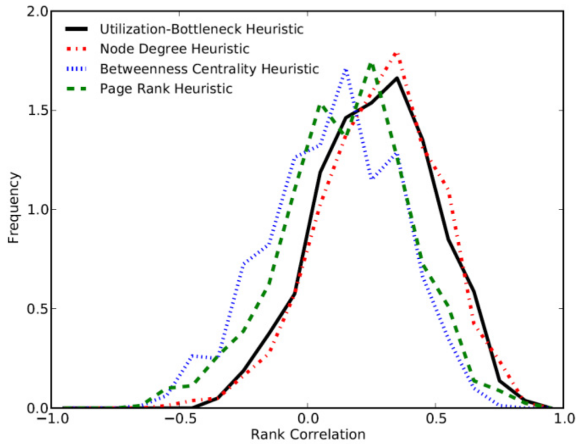

Fig. 4: Histogram of Rank Correlations between work system order predicted by heuristics and order of work systems in terms of throughput enhancement, when batching was applied ($\alpha = 1.4$).

		Capacity Increase			Batching		
Heuristic	**α**	p_{25}	p_{50}	p_{75}	p_{25}	p_{50}	p_{75}
Bottleneck Heuristic	1.0	0.6529	0.7462	0.8062	0.2411	0.4109	0.5594
	1.2	0.6421	0.7431	0.8200	0.1713	0.3098	0.4534
	1.4	0.6879	0.7819	0.8583	0.1111	0.2794	0.4294
	1.6	0.7532	0.8303	0.8846	0.1140	0.2617	0.4070
Node Degree Heuristic	1.0	0.6119	0.7004	0.7645	0.2322	0.3950	0.5465
	1.2	0.5877	0.6880	0.7500	0.1723	0.3225	0.4739
	1.4	0.5296	0.6325	0.7126	0.1255	0.2957	0.4499
	1.6	0.4470	0.5726	0.6736	0.0993	0.2565	0.4056
Betweenness Centrality Heuristic	1.0	0.0737	0.2085	0.3225	-0.0503	0.1412	0.2958
	1.2	0.0201	0.1499	0.2911	-0.0275	0.1354	0.2839
	1.4	-0.0202	0.1085	0.2259	-0.0779	0.1191	0.2934
	1.6	-0.1100	0.0202	0.1373	-0.0982	0.0485	0.2377
PageRank Heuristic	1.0	0.1879	0.3244	0.4704	0.0323	0.2038	0.3729
	1.2	0.2095	0.3500	0.4787	0.0196	0.1843	0.3433
	1.4	0.2512	0.3946	0.5249	-0.0053	0.1664	0.3212
	1.6	0.3065	0.4256	0.5330	-0.0353	0.1397	0.2912

Table 1: Correlation percentiles for the investigated heuristics and different values of alpha.

5. Conclusion and Research Outlook

The utilization bottleneck heuristic outperforms any other performance improvement heuristic in the example networks where bottleneck capacities were increased. However, it struggles to rank worksystems by their impact on performance under the batching rule, while there also is no alternative outperforming measure. Our results show that both the existing bottleneck heuristic and the here tested alternative measures of network centrality, have difficulties to predict the impact of batching induced flow variability. Our results also show that network measures are capable of enriching existing bottleneck identification heuristics in certain scenarios. More precisely, in situations where utilization and capacity data is not available (e.g., in a very early stage of manufacturing system design when no dynamic data is available), the node degree heuristic offers an easy-to-use assessment of the need to increase capacity at certain work stations, followed by more precise, but also costlier investigation of the circumscribed work stations. Further development of the PageRank metric, focusing on material flows rather than on node connections could prove to deliver more accurate results.

By describing and analyzing the problem of bottleneck identification as a problem of network design and network interaction, we further demonstrate and explore the inherent relationship between complex network theory and manufacturing systems, as well as move network theoretic considerations closer to practical application in the domain.

Further research will include the investigation of the applicability in real manufacturing networks, also on dynamic data sets. A deeper investigation of different network topologies, according to the assumption presented in Section 3, and the effectiveness of the selected measures can provide additional insights into the applicability and predictive power of network metrics in bottleneck identification in a manufacturing context.

While the existing simulation model could easily be extended to test further network metrics like Freeman's closeness or Eigenvector centrality [11] and a more varied choice of capacity adjustment rules through, e.g., technological rather than dynamic adjustments, the considerations in [11] and the results shown here motivate a differentiated approach to using network theory and its metrics in the field of manufacturing systems. A bottom-up understanding of the network dynamics is required in order to identify and/or purpose-build network measures that can predict network flows in manufacturing scenarios.

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